Critical Events in Mechanically Ventilated Patients

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Abstract. Mechanical Ventilation is an artificial way to help a Patient to breathe. This procedure is used to support patients with respiratory diseases however in many cases it can provoke lung damages, Acute Respiratory Diseases or organ failure. With the goal to early detect possible patient breath problems a set of limit values was defined to some variables monitored by the ventilator (Average Ventilation Pressure, Compliance Dynamic, Flow, Peak, Plateau and Support Pressure, Positive end-expiratory pressure, Respiratory Rate) in order to create critical events. A critical event is verified when a patient has a value higher or lower than the normal range defined for a certain period of time. The values were defined after elaborate a literature review and meeting with physicians specialized in the area. This work uses data streaming and intelligent agents to process the values collected in real-time and classify them as critical or not. Real data provided by an Intensive Care Unit were used to design and test the solution. In this study it was possible to understand the importance of introduce critical events for Mechanically Ventilated Patients. In some cases a value is considered critical (can trigger an alarm) however it is a single event (instantaneous) and it has not a clinical significance for the patient. The introduction of critical events which crosses a range of values and a pre-defined duration contributes to improve the decision-making process by decreasing the number of false positives and having a better comprehension of the patient condition.

Keywords: Critical Events, Intensive Care, INTCare, Ventilated Patients, Data Acquisition, Real-Time, Streaming Data, Interoperability.

1. Introduction

The process of ventilating a patient using artificial techniques is complex and it involves a set of concerns. By default a set of variables is defined in the ventilator according to the patient needs. Then the ventilator is prepared to monitoring the patient condition by collecting a set of patient values (e.g. Plateau Pressure, PEEP, Respiratory Rate, others). Typically these data are shown in the ventilator monitor and they are partial recorded (only the first value of the hour is considered) in an electronic platform or manual sheet.

To a better decision it is fundamental to have a system able to collect and process the data in real-time. In this sense a data acquisition architecture was designed. The architecture developed uses interoperability, streaming data and intelligent agents to store the patient data in the database. After this process a huge volume of data is available to be consulted by the clinicians in order to make the best decision. However and although the high number of data available, the physicians do not have time to read and understand all the data available in the right moment. In order to support and facilitate this analysis the Critical Events (CE) concept [1] was adopted and it was associated to ventilation variables. The concept was initially applied to vital signs variables [2]. This process was defined using the knowledge obtained through a literature review and after meeting with physicians. The process was tested and it was defined taking in attention the Intensive Care Units (ICUs) particularities.

ICU is a unit where the patients with severe diseases are admitted. In most cases they are needing mechanical ventilation. This work is framed in the INTCare project [3, 4] and it was evaluated using real data provided by the Intensive Care Unit of Centro Hospitalar do Porto, Hospital Santo António. The introduction of critical events [5, 6] has as main goal decreasing the number of false positives and finding an alternative way to avoid the noise alerts presented in the ventilators [7]. Generally the alerts are turned off because they are very noisy and they interfere in the environment. With this new solution an event only is considered serious if a patient has a critical value for a pre-defined period of time. This solution contributes to outwit false positives provided by the ventilator. All the values collected are validated before being used by the agent responsible to categorize the value as critical or not.

As already mentioned all the definition process was based in clinical evidences. The definition of the values was made after meetings with the intensivists and after reading clinical works.

The goal of this work was achieved and as result the critical events concept was defined to mechanically ventilated patients. At same time a platform was developed to show the results and alert the clinicians about the patient condition, i.e., when the patient is with a critical event.

This paper is divided in seven sections. After a brief introduction of the work the concepts are addressed and the project is presented in section 2. Section 3 presents the data acquisition architecture designed. Section 4 presents the critical events ranges and how it is calculated. Then in section 5 a dataset was analysed in terms of critical events and their results are presented. Section 6 makes a conclusion of the work and finally in section 7 there is some points of future work.

2. BACKGROUND

2.1 Mechanical Ventilation

A patient is connected to a ventilator when he cannot breathing from natural ways. Mechanical ventilation is used to support the patient in their respiratory functions.

Mechanical ventilation in Intensive Care Units is considered an essential, life-saving therapy for patients with critical illness and respiratory failures [8].

The ventilators were developed with a second goal: to generate alarms when patients become disconnected or they are having critical ventilator events [7]. "All ventilators are now designed to detect critical events and are equipped with alarms. However, these alarms are only audible peeps that often are difficult to hear outside of the patient's room. Moreover, the large number of false-positive alarms generated by bedside monitoring devices exacerbates this problem because ventilator alarms can blend in with other accustomed sounds of the intensive care unit" [7].

According to a CDC study [8] Ventilator-associated pneumonia (VAP), sepsis, Acute Respiratory Distress Syndrome (ARDS), pulmonary embolism, barotrauma, and pulmonary edema are among the complications that can occur in the patients. The ventilator events are identified by using a combination of objective criteria: deterioration in respiratory status after a period of stability or improvement on the ventilator, evidence of infection or inflammation, and laboratory evidence of respiratory infection [8].

In this work and having in consideration the definitions above mentioned the goal is to give a new importance to the variables continuous monitored by the ventilator. By combining the values and their duration it is possible defining a set of values from a specific variable as a critical event.

2.2 Intensive Care Units

Intensive Care Units (ICUs) provide intensive care (treatment and monitoring) for people in a critically ill situation or unstable condition [2]. In ICUs are patients which needs a continuing medical attention and support to keep their body functioning (e.g. respiratory system). This type of support is essentially done recurring to technology and to the care of intensivists (nurses and physicians) [9].

Respiratory failure is one of the most common causes of ICU admission and 75% of the patients require mechanical ventilation. Despite of their benefits, these procedures might have some serious drawbacks like contributing to the lung's injury. Mechanical ventilation can have negative effects and its mortality rate ranges from 41% to 65% [10]. The number of re-intubations vary from 2% to 25% [11].

An automatic control of the mechanical ventilation can significantly improve the patient care in the ICUs, reduce the mortality and morbidity rates associated with provision of inappropriate ventilator treatments and reduce healthcare costs.

2.3 INTCare

INTCare is a research project designed to Intensive Care Medicine. This project gave origin to two platforms: patient monitoring and decision support. INTCare architecture is based in a multi-agent system [12].

Using INTCare is possible monitoring patients in real-time. It is possible store, process and analyse data automatically collected from bedside monitors (vital signs and ventilators), therapeutics and laboratory or manually recorded in the platform.

Using intelligent agents all the data are processed and a set of indicators and medical scores is presented to the intensivists.

The second platform is an Intelligent Decision Support System (IDSS). This platform uses ensemble data mining to predict clinical events (e.g. organ failure, patient outcome, length of stay, barotrauma among others). The use of critical events [1, 13] improves the sensitivity of the data mining models [1, 14-16]. Now this project is focused in the respiratory system and in predicting the occurrence of barotrauma [17]. With the development of this new approach and the definition of critical events to the ventilation, the influence of these variables will be studied in the models already induced [18-20].

3. Data acquisition architecture

This section presents the architecture (Figure 1) developed to collect the data from the ventilators using data streaming. To support this architecture a set of intelligent agents [21, 22] is used. First a ventilator is connected to a patient. This ventilator is able to monitoring all the patient respiratory variables. To have a correct identification of the patient, a procedure is used to confirm which patient is using the ventilator. This procedure will consult the Electronic Health Record (EHR) and analyse which patient is admitted in the bed near the ventilator that is collecting the data.

Then the gateway is prepared to send a message to the ventilator with the information about which variables were chosen to be collected. Then and after the ventilator receives the message all the results associated to the variables chosen are sent by the ventilator to the gateway. This process is continuous. Then the received results are processed by the Ventilation Acquisition agent in order to create Health Level Seven (HL7) [23] messages. This message is divided in two levels: header and data. After these messages be stored in the temporary tables a pre-processing agent is executed to analyse the values. This agent has the responsibility to verify if a value is valid and if it is critical or not. Then the pre-processing agent will analyse the last values collected and verify if they can be considered a critical event or not. The pre-processing agent uses the data presented in the critical events table (table 1) to make their job. This agent is responsible by understanding the significance of a value in a specific variable (each time a new value arrives). When a value lower or higher than the normal range appears for the first time, this agent starts recording an event. Then all the values collected are analysed. The event will be closed only (with a finish date) when a normal value arrives, until then the agent will continue counting the event duration. After finishing the event, the agent will verify the significance of the event duration. If the event duration is higher than the time defined as normal, the event is considered critical, otherwise it is normal.

Finally the information attained (events data) by the agent is stored in the database.

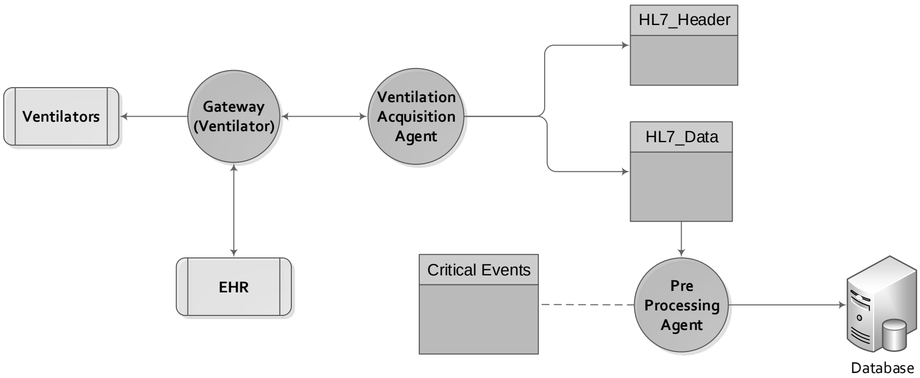


Figure 1. Data Acquisition Architecture

4. Critical Events in ventilation

As mentioned the critical events (CE) range were defined after a depth literature review about the influence of each variable has in the patient condition and a meeting with experts in this area.

Table 1 presents a set of variables that can be used to define critical events. The Min Normal and Max Normal are the normal values (range). The columns Min and Max value are used to validate the values, i.e., it is the minimum and maximum value that a ventilator can monitoring. The values out of this range are considered noise values and they are not considered in the CE calculation process. The time (in minutes) is used to define an event as critical.

To calculate the CE an agent is used. The pre-processing agent is responsible by verifying if a set of values are lower than Min Normal or Higher than Max Normal with a duration upper than the time defined. Firstly this agent has to validate the values collected and verify if each value collected is in the normal range. Then if both conditions are verified a critical event is defined.

For example in the case of Positive end-expiratory pressure (PEEP) an event is considered critical when a patient has a PEEP higher than 0 and lower than 20 and at same time all the values collected are lower than 5 and upper than 15 for a period higher than 10 minutes.

Table 1. Ventilation critical events definition

Variable	*Units*	*Min Normal*	*Max Normal*	*Min Value*	*Max Value*	*Time*
Average Ventilation Pressure (AVP)	cmH2O	6	25	0	40	10
Compliance Dynamic (CDYN)	mL/cmH2O	21	43	0	250	30
Flow	litters per minute	20	80	20	250	10
Peak Pressure	cmH2O	8	50	0	100	10

Variable	Units	Min Normal	Max Normal	Min Value	Max Value	Time
PEEP	cmH2O	5	15	0	20	10
Plateau Pressure	cmH2O	8	30	0	100	10
Respiratory Rate	breaths per minute	8	25	1	200	10
Support Pressure	cmH2O	6	26	1	100	10

5. Data Analysis

After create the CE it was possible to make an analysis of the data collected using real data provided by ICU of Centro Hospitalar do Porto. This analysis had in consideration the data collected from 2015, 1, January and 2015, 31, June. This data corresponds to 67 ventilated patients.

Table 2 presents the number of values collected and how many values are critical. Then it was studied the values duration and if they can represent a critical event. In the critical events column it is the number of events categorized as 1 (critical). In the column Critical Events Time is the number of events categorized as 1 and they had a duration upper than the time presented in table 1. The percentage represents a values ratio. This ratio is presented in figure 2.

As can be observed in table 2, Compliance Dynamic (CDYN) is the variable which present more values out of the normal range with a percentage of 41.79%.

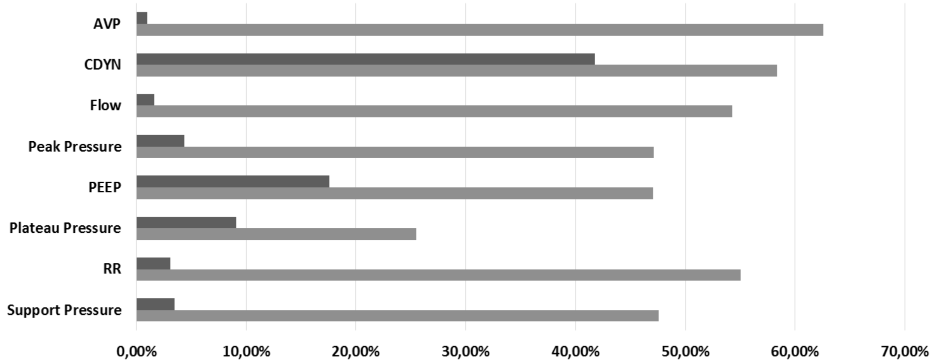
In the case of Critic Events is interesting verify than in average most of the events are not critical, i.e., they did not have a significant duration. In this case Average Ventilation Pressure (AVP) is the most critical variable with a percentage of critic events higher than 62%.

It is important to note that the normal events (values between the normal ranges) were not considered in this analysis.

Table 2. Ventilation Values and Critical Events in an ICU

Variable	Critical Value	All Values	Critical Value%	Critical Events Time	Critical Events	Critical Events Time %
AVP	618	61733	1.00%	545	871	62.57%
CDYN	24360	58293	41.79%	522	895	58.32%
Flow	848	51311	1.65%	19	35	54.29%
Peak Pressure	2708	61653	4.39%	365	775	47.10%
PEEP	10910	61985	17.60%	32	68	47.06%
Plateau Pressure	5584	61312	9.11%	103	404	25.50%
RR	1576	50768	3.10%	44	80	55.00%
Support Pressure	510	14639	3.48%	29	61	47.54%

Figure 2 presents the number of critical events verified in this ICU during the last 6 months. For example analysing the Plateau Pressure there is a considerable number of critical values (9.11%) but from these only 25.5% has a duration upper than 10 minutes and it is considered a critical event. In the opposite site it is AVP with 1% of critical values being 62.57% of these values considered as critical events.



	Support Pressure	RR	Plateau Pressure	PEEP	Peak Pressure	Flow	CDYN	AVP
■ Critical Values	3,48%	3,10%	9,11%	17,60%	4,39%	1,65%	41,79%	1,00%
■ Critical Events	47,54%	55,00%	25,50%	47,06%	47,10%	54,29%	58,32%	62,57%

Figure 2. Data analysis distribution

6. Conclusion

In this work a new concept was associated to mechanical ventilation. Critical Events were introduced in order to better categorize a patient. CE help the intensivist to have a better comprehension of patient condition without to have to look to the ventilator all the time.

As mentioned in the background, typically the ventilator alarms are shut down due to their noise. With this new concept, a set of patient values can be considered a critical event or not instead of being used a single value.

Intelligent Agents are used to process all the results collected automatically and in real-time. These agents follows a set of rules pre-defined. First the values are validated and categorized as critical or not using table 1 by the agent. Then and having in consideration the event duration a set of values is defined as critical or not. As can be observed in the analysis made there are a set of patients values that are constant collected and can active an alarm but they are considered a noise value.

With this new concept only the values with clinical relevance are considered – in case of a patient is suffering a values variation out of the normal range for a determined period of time. With this work it was also possible observe a set of negative values, i.e., out of the acceptable range (e.g. plateau pressure equal to - 9). Beside this fact validating the values is true important in order to avoid false positives and to have a correct calculation of critical events.

The system developed is intelligent because it is able to analyse the values collected, understanding if it is or not critic basing their decision in the value range and in the event duration. In parallel it is able to automatically and in real-time processing all the values collected and send alerts when some abnormal value is verified or a patient is in risk due to the event duration. A patient tracking system [24] also was developed using the concept presented in this paper.

Some study are being performed using Critic Events [25]. Data Mining models are being induced and the results are very promising (blood pressure [26] , arrhythmias [27]).

The goal of this paper was not to study the Critical Events impact but analyse the possibility to introduce CE in the ventilation variables. Section 5 was fundamental to present a possible analysis of the data collected using the CE concept. As main contribution of this work it is the definition of critical events to ventilation and their applicability in the Intensive Care Units. With this work the researchers has a new approach that can be considered in future studies.

7. Future Work

In the future it is fundamental study the real influence of critical events in the patient condition by developing data mining models using this variable. For example CE can be used to improve Data Mining models in order to predict Barotrauma or Early extubation. At same time it is necessary to finish the development of the alert platform.

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